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AI-Driven Optimization of Maximum Power Point Tracking (MPPT) for Enhanced Efficiency in Solar Photovoltaic Systems: A Comparative Analysis of Conventional and Advanced Techniques

Val Hyginus Udoka Eze[1]*, Pius Erheyovwe Bubu[1], Charles Ibeabuchi Mbonu[2], Ogenyi Fabian C[1] and Ugwu Chinyere Nneoma[1]

[1]Department of Electrical, Telecom. & Computer Engineering, Kampala International University, Uganda
[2]Department of Electrical and Electronic Engineering, Federal University of Technology Owerri, Imo State
***Corresponding Author: Val Hyginus Udoka Eze, udoka.eze@kiu.ac.ug, Kampala International University, Western Campus, Ishaka, Uganda (ORCID: 0000-0002-6764-1721)**

ABSTRACT

The growing global demand for clean, sustainable energy has driven extensive research into renewable energy technologies, with solar energy emerging as a highly promising solution. Solar photovoltaic (PV) systems are increasingly adopted for their ability to convert sunlight into electricity, providing an environmentally friendly alternative to fossil fuels. However, the performance of PV systems is significantly influenced by environmental factors, particularly solar irradiance and temperature, which lead to fluctuations in power output. This study explores the application of Artificial Intelligence (AI)-based Maximum Power Point Tracking (MPPT) techniques to optimize the efficiency of PV systems. AI-driven MPPT controllers, incorporating machine learning, fuzzy logic, and genetic algorithms, offer enhanced adaptability, responsiveness, and efficiency compared to traditional methods. The research focuses on the design, development, and evaluation of an AI-optimized MPPT controller prototype, demonstrating the potential of AI to overcome the limitations of conventional MPPT techniques. This optimization enhances the efficiency, stability, and scalability of solar energy systems, particularly in rural electrification and industrial energy management. Among traditional MPPT methods, the Optimized Adaptive Differential Conductance (OADC) technique is notable for its simplicity, cost-effectiveness, and ease of implementation, while the Scanning Particle Swarm Optimization (SPSO) technique stands out for its superior tracking accuracy and ability to achieve real-time convergence to the Maximum Power Point.

Keywords: Artificial Intelligence, Maximum Power Point Tracking, Solar Photovoltaic Systems, Machine Learning, Fuzzy Logic, Genetic Algorithms, Renewable Energy

INTRODUCTION

The increasing global demand for clean and sustainable energy sources has intensified research into renewable energy technologies, with solar energy emerging as one of the most promising solutions [1]. Solar photovoltaic (PV) systems have gained widespread adoption due to their ability to directly convert sunlight into electricity, offering a renewable and environmentally friendly alternative to fossil fuels [2,3,4,5]. However, the efficiency of PV systems is highly dependent on environmental conditions, particularly solar irradiance and temperature variations, which significantly influence power output [6,7]. These fluctuations pose a challenge in maintaining maximum power extraction, necessitating the implementation of effective control strategies to enhance system performance. Maximum Power Point Tracking (MPPT) techniques are essential for optimizing power generation in PV systems by dynamically adjusting the operating point to extract the highest possible power [8,9,10]. Conventional MPPT algorithms, such as Perturb and Observe (P&O) and Incremental Conductance (INC), have been widely employed due to their simplicity and ease of implementation [2]. However, these methods exhibit limitations, including slow convergence rates, steady-state oscillations, and reduced tracking

accuracy under rapidly changing weather conditions. Such drawbacks hinder the efficiency and stability of PV systems, particularly in applications requiring high reliability, such as microgrids and remote power systems [9,10]. Recent advancements in Artificial Intelligence (AI) have introduced novel approaches to overcoming the limitations of traditional MPPT techniques. AI-based methods, including machine learning algorithms, fuzzy logic controllers, and artificial neural networks (ANNs), offer enhanced adaptability and responsiveness to dynamic environmental conditions [12]. These intelligent MPPT controllers can predict optimal operating points, reduce tracking errors, and improve the overall efficiency of PV systems. The integration of AI into MPPT not only enhances energy harvesting capabilities but also contributes to the development of smarter and more resilient renewable energy systems [2]. This study focuses on the design, development, and fabrication of an AI-driven MPPT controller aimed at optimizing PV system performance. The research objectives include designing an MPPT system that incorporates AI-based optimization techniques, fabricating a functional prototype using embedded systems and advanced power electronics, evaluating its performance against conventional MPPT techniques, and exploring its scalability for applications in rural electrification and industrial energy management. By leveraging AI-driven MPPT controllers, this research aims to contribute to the advancement of efficient and intelligent solar energy systems, fostering sustainable energy solutions for diverse applications.

Advanced MPPT Algorithms

Maximum Power Point Tracking (MPPT) is essential for optimizing energy harvesting from solar panels. Traditional algorithms like Perturb and Observe (P&O) and Incremental Conductance (Inc-Cond) are effective in stable conditions but struggle with fluctuating environmental factors. Advanced MPPT algorithms, utilizing techniques like machine learning, fuzzy logic, and genetic algorithms, offer real-time adaptation to varying conditions [2]. These algorithms improve efficiency by predicting optimal performance and making dynamic adjustments, leading to better energy harvesting and system resilience. They represent a shift towards smarter, more efficient solar power systems.

Conventional (Non-Intelligent) MPPT Techniques

Traditional Maximum Power Point Tracking (MPPT) techniques aim to optimize the power extraction from photovoltaic (PV) systems by dynamically adjusting the operating voltage or current. The most commonly used conventional MPPT algorithms include:

Perturb and Observe (P&O)

The Perturb and Observe (P&O) technique operates by continuously adjusting the photovoltaic (PV) panel's operating voltage to maximize power extraction. This is achieved by incrementally perturbing the PV array's voltage and observing the resulting change in power (ΔP) [14]. A positive change in power indicates that the voltage perturbation is moving the operating point (OP) closer to the Maximum Power Point (MPP), suggesting that further perturbation in the same direction will accelerate convergence to the MPP [12,13]. Conversely, a negative change in power signifies that the OP has deviated from the MPP, necessitating a reversal in the perturbation direction to guide it back toward optimal power output, as illustrated in Figure 1. The fundamental principle and operation of the P&O algorithm are further detailed in Equation (1).

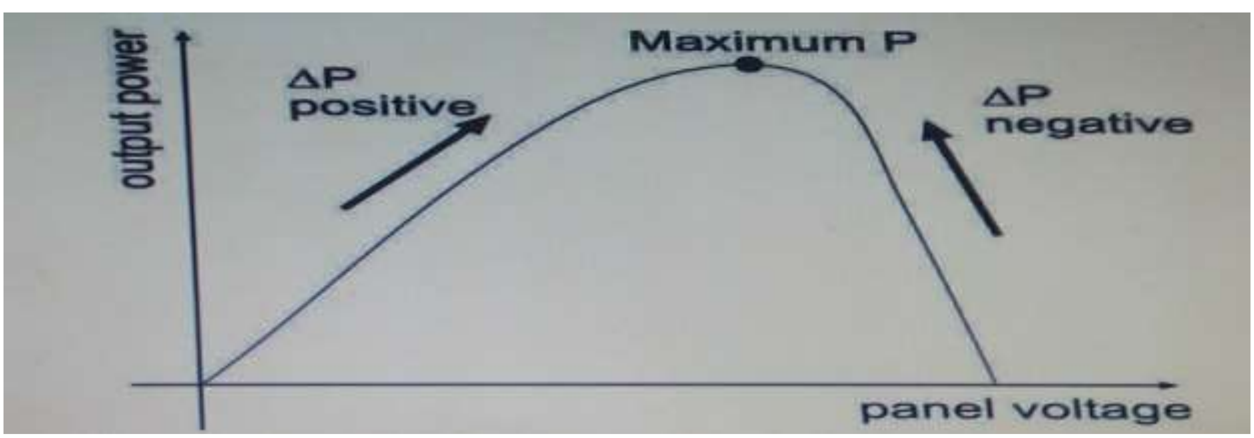

Figure 1: P-V Characteristics for P&O Algorithm [14,10]

Equation (1) shows the working principle of the perturb & observe algorithm. The algorithm continuously decrements or increments with respect to reference voltage based on the previous data until

the MPP is attained. When $\frac{dP}{dV} > 0$, the operating voltage of the Photovoltaic array will be perturbing within a specified direction, which implies that perturbation moves the operating point of the Photovoltaic array towards the MPP. The Perturb & Observe technique, therefore, will continue to hover the PV voltage in the direction of the MPP. The reverse is the case when $\frac{dP}{dV} < 0$, MPPT frequency or perturbation frequency is the number of valid perturbations covered by the Maximum power point tracking algorithm per second [14].

$$\left.\begin{array}{c} When\ \Delta P\ < 0, V(j) > V(j-1), then\ Vref\ = V(j+1)\ =\ V\ (j)\ -\ \Delta V \\ When\ \Delta P < 0, V(j) < V(j-1), then\ Vref\ = V\ (j+1)\ =\ V\ (j)\ + \Delta V \\ When\ \Delta p > v(j) < v(j-1), therefore, Vref\ = v\ (j+1)\ =\ v\ (j)\ -\ \Delta v \\ When\ \Delta P > 0, V(j) > V(j-1), then\ Vref\ = V\ (j+1)\ =\ V\ (j)\ + \Delta V \end{array}\right\} \quad (1)$$

Incremental Conductance (INC)

The Incremental Conductance (INC) algorithm is an improved MPPT technique that overcomes some limitations of the Perturb and Observe (P&O) method by using a more analytical approach to determine the Maximum Power Point (MPP). It achieves this by analyzing the relationship between incremental conductance and instantaneous conductance as shown in Equation (2). When these values are equal, the system is operating at the MPP. If the operating point is at the left of the MPP, an increase in voltage is required whereas when it is at the right of the MPP a decrease in voltage is required as shown in equation (3) [14,15].

$$\frac{dI}{dv} = -\frac{I}{v} \quad At\ MPP \qquad (2)$$

$$\left.\begin{array}{ll} \frac{dI}{dv} > -\frac{I}{v} & left\ of\ MPP \\ \frac{dI}{dv} < -\frac{I}{v} & Right\ of\ MPP \end{array}\right\} \qquad (3)$$

Where; V is the Voltage and I is the Current

This method enables more accurate tracking of the MPP, particularly under rapidly changing irradiance conditions, as it eliminates steady-state oscillations that affect P&O as shown in Figure 2. However, INC is computationally more demanding and can exhibit slower response times in highly dynamic environments [10]. Despite this, its improved accuracy makes it a preferred choice for applications where precise power tracking is crucial, such as grid-connected PV systems and hybrid renewable energy setups.The P&O MPPT regulates the PWM control signal until the condition $\frac{dI}{dV} + \frac{I}{V} = 0$ is satisfied.

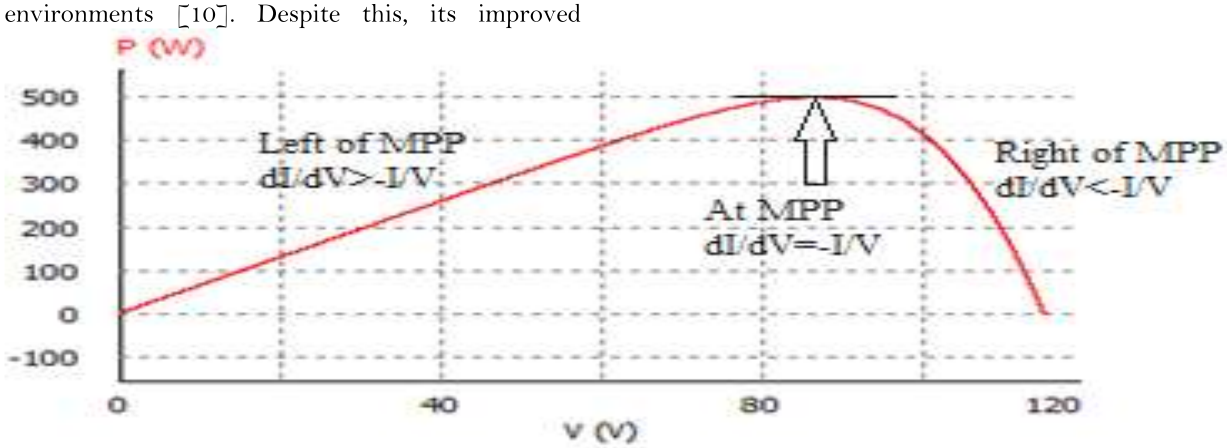

Figure 2: P-V Characteristic for Incremental Conductance Algorithm [10,14]ss

Optimized Adaptive Differential Conductance (OADC) Technique

This OADC mathematical model in equation (4) was computed using single diode model. It deals with comparing and balancing the impedance of the load with the impedance of the solar PV panel with respect to their respective conductance. The major difference between this technique and the existing conventional INC technique was that conventional INC differentiated the current and the voltage while

OADC differentiated current and voltage at its maximum power points. The advantage of OADC is that it accurately detects the MPP without much delay but it has a major drawback of low power conversion. This low power conversion has led to more research in this area to improve the power generated and transferred to the load.

$$\Upsilon = \left(\frac{I_{mpp}}{V_{mpp}} - \frac{dI}{dV}\right)$$
$$= \frac{\left(\frac{\alpha nKT}{qR_s}\, log_e\left(1+\frac{1}{1000I_o}\right)\left[1+k_i\left(T-T_{ref}\right)\right]\frac{G}{G_{ref}}\right) - \mathrm{Io}\left[exp\left(\frac{qV_{mpp}}{\alpha nKT}\right)\right]}{V_{mpp}}$$
$$-\frac{I_o q}{\alpha nKT}\exp\left(\frac{Vq}{\alpha nKT}\right) \qquad (4)$$

The resulting conductance in this technique is determined by the instantaneous panel conductance $\left(\frac{I_{mpp}}{V_{mpp}}\right)$ and load conductance $\frac{dI}{dV}$, as expressed in equation (4), where Υ represents the resultant conductance. Ideally, for equation (4) to be satisfied, the resultant conductance must be zero [10]. Table 1 shows the comparison of the most popular conventional MPPT Algorithms.

Table 1: Comparison of P&O, INC and OADC [14,8]

Specification	**P&O**	**INC**	OADC
Efficiency	Medium about 95%, depending on the optimization method	High about 98%, depending on the optimization method	Excellent (98.5%)
Complexity	Easy	Yes	Medium
Implementation	Easy to implement as few parameters are measured	Complex as the microcontroller is used	Complex as complex algorithm is used
Cost	Low	Medium	
Accuracy	Medium	High	Very High
Advantages	Low cost, easy to implement	No oscillation, easy to implement	It locates MPP accurately and has a very good converging speed
Drawbacks	Difficult to locate MPP	Expensive and inability to detect the MPPT accurately during rapidly varying atmospheric conditions for	Has low generated and transferred power

AI-Based (Intelligent) MPPT Techniques

The proposed AI-optimized MPPT controller integrates cutting-edge computational intelligence techniques to maximize solar energy harvesting and improve adaptability in varying environmental conditions. This system combines Machine Learning (ML), Fuzzy Logic (FL), and Genetic Algorithms (GA) to dynamically predict, optimize, and control the MPPT process. Here's a deeper exploration of each component.

Machine Learning (ML)

Machine learning (ML) algorithms have emerged as a powerful tool for improving MPPT performance by leveraging data-driven approaches to predict and track the Maximum Power Point (MPP). ML-based MPPT controllers, such as regression models and neural networks, are trained on large datasets that include historical and real-time data on solar irradiance, temperature, and system performance metrics. These models learn from past behavior and continuously adapt to changes in environmental conditions, such as cloud cover or seasonal variations, enabling the MPPT system to optimize power output even under dynamic and unpredictable weather patterns [16,17]. The primary advantage of using machine learning in MPPT is its **data-driven approach**, which allows the system to adapt to a wide range of environmental conditions. The model can be trained on extensive datasets containing various weather scenarios and solar panel performance, enabling it to generalize and perform efficiently in diverse conditions. Additionally, ML-based systems benefit from **predictive power**—the ability to forecast the optimal operating point of the system even without perfect knowledge of future weather conditions [17]. This capability enables the MPPT controller to make intelligent adjustments in real-time, maximizing energy production and enhancing the system's overall efficiency. The adaptability and precision of machine learning make it a promising solution for advanced MPPT applications, particularly in complex and variable environments,

such as remote areas or regions with highly fluctuating weather patterns.

Fuzzy Logic (FL)

Fuzzy Logic (FL) offers a powerful approach to MPPT by providing robust decision-making capabilities in environments characterized by uncertainty and imprecision, which are common in renewable energy systems. In solar energy systems, environmental factors like fluctuating sunlight, temperature variations, and changing load demands introduce ambiguity that can challenge conventional MPPT methods [18,2,14]. Fuzzy Logic, with its tolerance for such uncertainty, ensures that the MPPT algorithm adjusts smoothly and efficiently in response to these dynamic conditions, leading to better power extraction. Figure 3 represents the Block Diagram of the Designed Fuzzy Logic MPPT System.

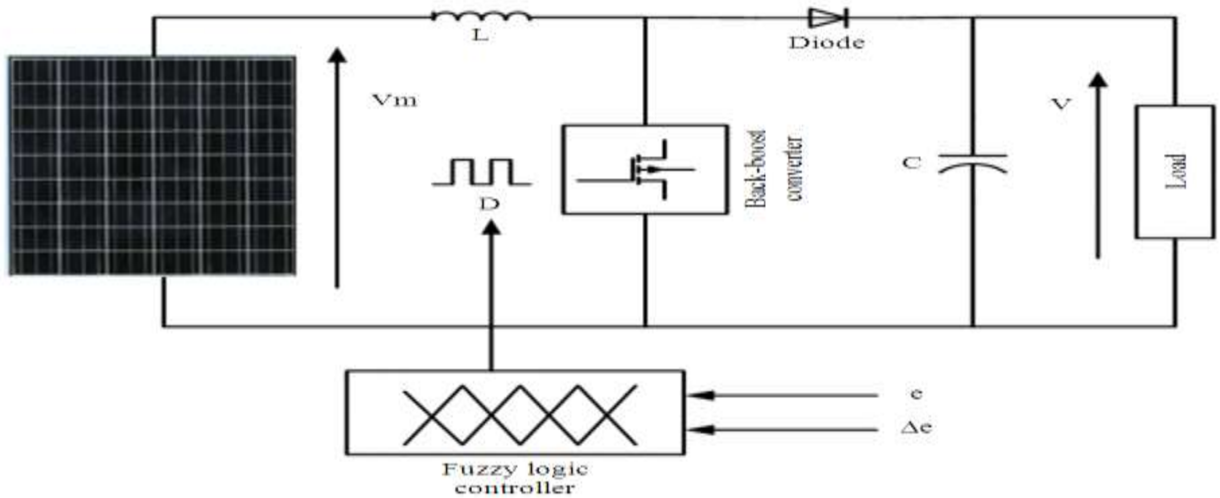

Figure 3: Block Diagram of Designed Fuzzy Logic MPPT System

A key feature of FL is its **rule-based reasoning**, where fuzzy rules (e.g., "If solar irradiance is high, then increase voltage input") are applied to make real-time control adjustments. These rules enable the system to continuously adapt to the varying conditions, ensuring the MPPT controller tracks the MPP more accurately [19,20]. Furthermore, FL's tolerance to uncertainty allows it to operate effectively even when measurements are not exact or fluctuate due to environmental changes. This reduces the reliance on precise inputs, making it especially useful in scenarios where accurate real-time data is not always available. FL's ability to manage and adapt to uncertainty makes it highly effective in maximizing the performance of solar power systems, providing smoother, more reliable operation compared to traditional algorithms under variable conditions.

$$E(k) = \frac{P(k) - p\,(k-1)}{V(k) - V\,(k-1)} \qquad (4)$$

$$\Delta E(k) = E(k) - E(k-1) \qquad (5)$$

The fuzzy controller for solar Maximum Power Point Tracking (MPPT) utilizes two input variables: error (E) and change in error (ΔE). The selection of the error input depends on the designer's expertise and the specific characteristics of the solar PV system. A common approach is to define the error as the slope of the power-voltage (P-V) curve, dP/dVdP/dV, since it equals zero at the Maximum Power Point (MPP), as expressed in Equation (4). The change in error (ΔE) represents the difference between successive error values and is defined in Equation (5).

Genetic Algorithm (GA)

Genetic algorithms (GA) offer a powerful optimization technique for improving the performance of MPPT controllers by dynamically adjusting key system parameters, such as voltage and current thresholds [21]. GAs simulate natural evolutionary processes, including selection, crossover, and mutation, to evolve a population of candidate solutions over successive generations. This iterative process allows the algorithm to identify the most optimal settings for the MPPT controller based on system performance and environmental conditions. A significant advantage of using GA in

MPPT is its **dynamic optimization** capability. By continuously fine-tuning the control parameters in real-time, GA adapts to changing environmental factors and system behavior, ensuring that the system operates at maximum efficiency. Additionally, GA's **global search capability** distinguishes it from traditional MPPT methods like Perturb and Observe (P&O). While P&O typically operates within a limited search space, GA can explore a broader range of possible solutions, allowing it to converge on a more optimal solution, particularly in complex or highly dynamic scenarios [22]. This makes GA particularly useful in situations where environmental conditions vary greatly, enabling more precise and efficient tracking of the MPP. GA-based MPPT techniques offer greater flexibility and robustness, making them an ideal choice for advanced solar power systems that require high performance and adaptability.

Scanning Particle Swarm Optimization (SPSO) Technique

Scanning Particle Swarm Optimization (SPSO) is a metaheuristic optimization technique known for its high accuracy and superior performance in identifying the Global Peak (GP) while avoiding the pitfalls of getting trapped at Local Peaks (LP), which often occur in traditional Particle Swarm Optimization (PSO) methods. However, during Partial Shading Conditions (PSC), the position of the Global Peak shifts, complicating the ability of conventional PSO techniques to capture the new GP unless they undergo reinitialization. This reinitialization process introduces a delay in tracking the new GP, which may lead to premature convergence [23]. To address this challenge, a novel approach was introduced in [23], which enables the detection of the new GP without the need for reinitialization. The SPSO design works by directing a particle to the anticipated peak regions to search for a higher power peak than the current GP. If a new, higher GP is found, the PSO operating point is immediately shifted to this new peak. If the new GP is lower than the current one, it is discarded, and the old GP is retained. While this technique effectively prevents premature convergence a common issue with conventional PSO it does not fully resolve the problem of delayed convergence speed. The key limitations of SPSO include its slower convergence rate and increased programming complexity. Despite these drawbacks, SPSO's strong performance makes it a promising candidate for improvement, which is why it was selected for enhancement in this research. The goal is to address the issues of delayed convergence speed and programming complexity, ensuring faster and more efficient MPPT operation.

Table 2: Summary of MPPT Existing Technique [14]

MPP Technique	Efficiency	Convergence speed	Oscillation	Cost	Implementation complexity	Sensed parameters	Track real MPP	Reliability
P&O	Medium (95%)	Varies	No	Relatively lower	Low	Voltage	Yes	Low
INC	Max (98%)	Varies	No	Expensive	Medium	Voltage, Current	Yes	Medium
FSCC	Poor	Medium	Yes	Inexpensive	Medium	Current	No	Low
FOCV	Poor	Medium	Yes	Inexpensive	Low	Voltage	No	Low
PSO	Max (99.8)	Fast	No	Expensive	Medium (Digital)	Multi-variable	Yes	High
FLC	Max	Fast	Yes	Expensive	High (Digital)	Varies	Yes	Medium
ANN	Max	Fast	Yes	Expensive	High (Digital)	Varies	Yes	Medium
IINC	Max	Varies	No	Expensive	Medium (Digital)	Voltage, Current	Yes	High
AP&O	Medium	Fast	No	Expensive	High (Digital)	Current	Yes	High
IPSO	Max	Fast	No	Expensive	High (Digital)	Multi-variable	Yes	Medium
T-S fuzzy	Max	Fast	Yes	Expensive	High (Digital)	Varies	Yes	Low
MAPSO	Max	Fast	No	Expensive	High (Digital)	Multi-variable	Yes	Low
SPSO	Excellent (99.1%)	fast	No	Expensive	High (Digital)	Multi-variable	Yes	Medium
OADC	Excellent (98.5%)	Very fast	No	Moderate	Digital	Vmpp, Impp	Yes	High
ML	Excellent (98.9%)	Very fast	No	Expensive	Digital	Multi-variable	Yes	High

Table 2 shows that MPPT techniques can be broadly classified into two categories known as intelligent-based and non-intelligent-based methods. Among the non-intelligent MPPT techniques, the optimized adaptive differential conductance (OADC) method stands out due to its simplicity, cost-effectiveness, and ease of implementation. However, it still suffers from limitations such as reduced tracking speed under

Partial Shading Conditions (PSC) and suboptimal power conversion efficiency. Conversely, intelligent-based MPPT techniques have demonstrated superior performance compared to their non-intelligent counterparts. Among these, the Scanning Particle Swarm Optimization (SPSO) technique emerges as the most effective, owing to its high tracking accuracy and ability to achieve real-time convergence to the Maximum Power Point.

Integrating the AI Techniques

By combining machine learning (ML), fuzzy logic (FL), and genetic algorithms (GA), an AI-optimized MPPT controller can significantly enhance the performance of solar power systems [23,24]. The integration of these techniques enables the system to adapt dynamically to environmental conditions, ensuring that the MPPT controller adjusts in real-time to fluctuations in solar irradiance, temperature, and load demands. This adaptability improves the overall efficiency and power output of the solar system, especially in variable and unpredictable environments. Moreover, the system handles uncertainty and vagueness effectively, as each AI technique is capable of managing imprecise or incomplete data [21]. Fuzzy logic manages ambiguity in inputs, ML algorithms predict optimal points based on historical data, and GA searches for the best possible solution [24,25]. This collective strength ensures that the system remains robust under diverse and changing conditions, enhancing long-term reliability. Additionally, the combined capabilities of GA's global search, ML's predictive power, and FL's flexibility enable the system to achieve global optimization of control parameters, such as voltage and current thresholds. This allows the MPPT controller to explore a wide solution space and converge on the most efficient operating point, ensuring better accuracy and performance in varying operational scenarios. Integrating these AI techniques into MPPT control systems leads to more precise, efficient, and reliable MPPT performance, enhancing the overall effectiveness of solar power systems under both steady-state and dynamic conditions. This represents a significant advancement over traditional methods, offering a more intelligent and adaptive solution for maximizing solar energy harvesting.

Benefits

- **Improved efficiency**: AI-based techniques continuously optimize the MPPT process, enabling better energy harvesting from the solar array. Machine learning algorithms predict and adjust operating conditions in real-time, while genetic algorithms and fuzzy logic ensure the system operates at the optimal point, even as environmental conditions fluctuate. This leads to higher overall system efficiency and more reliable power generation.
- **Higher adaptability**: AI-driven MPPT systems can learn and adapt to changing environmental conditions, such as varying sunlight intensity, seasonal changes, and temperature fluctuations. These systems can also adjust to hardware degradation over time, ensuring that performance remains high even as components, like solar panels or batteries, age. This adaptability ensures long-term efficiency without requiring constant manual adjustments.
- **Reduced complexity**: AI-based MPPT methods streamline system operation by reducing the need for manual calibration and intervention. The system can automatically adjust its control parameters, such as voltage and current thresholds, based on real-time data and evolving environmental conditions. This automation simplifies maintenance, reduces human error, and makes the system more reliable and easier to manage in the long run.

Fabrication & Implementation

The Hardware Design of the AI-optimised MPPT Controller integrates advanced components and technologies to maximize solar power efficiency through real-time monitoring, data processing, and dynamic energy regulation [6,25]. Below is a detailed breakdown of the key hardware components and their functionalities.

a. Microcontroller/Embedded System

The microcontroller (either Arduino or STM32) serves as the central processing unit (CPU) for the MPPT controller, processing sensor data and implementing AI-based MPPT algorithms to optimize energy conversion. Arduino is particularly well-suited for simpler applications or prototyping due to its user-friendly design and ease of use, making it an ideal choice for basic MPPT systems [26,27,28,29,30]. In contrast, STM32 offers higher processing power and greater flexibility, making it the better option for advanced applications that require real-time optimization and the implementation of complex AI techniques such as machine learning, fuzzy logic, and genetic algorithms [31]. The microcontroller ensures seamless data acquisition and real-time processing, enabling the

system to dynamically adjust the MPPT parameters to maintain optimal performance as environmental conditions fluctuate. This capability ensures that the system operates efficiently under a wide range of conditions, maximizing the solar energy harvested.

b. Power Electronics

Metal-Oxide-SemiconductorField-Effect Transistors (MOSFETs) are used as high-efficiency switches to regulate the flow of power from the solar panel to the load or storage system. Their fast-switching speeds and low on-resistance make them ideal for energy regulation, minimizing energy loss and ensuring efficient power conversion. MOSFETs play a crucial role in maintaining the system's overall performance by enabling rapid and precise adjustments to the power flow [32,33]. DC-DC Converters are employed to adjust the voltage output to meet the specific requirements of the load or battery, either by stepping up (boosting) or stepping down (buck) the voltage [34,35]. Buck Converters are commonly used to reduce the voltage for battery charging or to supply power to a load, ensuring efficient energy transfer without excessive power loss. On the other hand, **Boost Converters** are used to increase the voltage, when necessary, particularly when the energy stored in the system requires higher voltage levels for efficient distribution or storage. Both types of converters operate with high efficiency, ensuring minimal losses during power conversion and optimizing the transfer of energy across the system. This ensures that the solar power system delivers stable and reliable energy to meet varying demands.

c. Sensors

Voltage and Current Sensors are integral to the monitoring and optimization of solar power systems, as they continuously track the output voltage and current from the solar panels. These sensors provide real-time data essential for power calculations and maximum power point (MPP) tracking, which is crucial for maximizing energy conversion efficiency. The Voltage Sensor measures the voltage across the solar panel, helping determine the operating point and track the MPP [36,37]. Accurate voltage measurement allows the system to adjust its parameters to optimize energy conversion and ensure efficient operation. Similarly, the Current Sensor measures the current, and when combined with the voltage data, it enables real-time power calculations using the formula as shown in Equation (6). This enables precise energy management, ensuring that the solar system operates at its optimal power point. High-accuracy sensors with wide measurement ranges are essential for maintaining reliable MPP tracking and ensuring the system performs optimally. These sensors ensure that fluctuations in both voltage and current are precisely captured, supporting the efficient and continuous operation of the solar power system.

$$P = V \times I \qquad (6)$$

Where; P is the output Power; V is the Voltage and I is the Current

d. Communication Interface

The Communication Interface of the MPPT system enables remote monitoring and performance analysis, providing users with critical insights into the system's status and efficiency. Equipped with IoT-enabled Monitoring, the MPPT controller allows for seamless connectivity and real-time monitoring through communication modules like ESP8266 or **ESP32** (for Wi-Fi) and SIM800 (for GSM) [38,39]. These modules facilitate communication between the MPPT system and external devices such as smartphones, tablets, or cloud servers, ensuring users can remotely access and manage the system's performance. Additionally, Data Logging continuously tracks essential performance metrics—such as voltage, current, temperature, and power output—in real-time, providing a detailed record that can be analyzed to optimize system performance and identify any issues [40,41]. With Cloud Integration using platforms like ThingSpeak, Blynk, or custom cloud-based solutions, users can access both real-time and historical data, track energy generation trends, and adjust system parameters from anywhere, ensuring optimal operation and flexibility [42,43]. This integrated communication interface enhances the system's usability, allowing users to make informed decisions, improve efficiency, and ensure the reliable production of solar energy.

e. Integration of Components

The integration of these components ensures the efficient operation of the AI-optimized MPPT controller by providing key functionalities that enhance system performance. Real-Time Data

Processing is facilitated by the microcontroller, which processes sensor data to adjust the MPPT algorithm, ensuring the system efficiently tracks the maximum power point. Dynamic Control is achieved through the use of MOSFETs and DC-DC converters, which regulate power conversion and adapt rapidly to fluctuating environmental conditions, ensuring optimal energy flow [34,35]. Additionally, Remote Monitoring is made possible through the IoT interface, allowing users to monitor and control the system remotely, thereby enhancing both user experience and system optimization. The Benefits of this integration include Efficient Power Management, as the system minimizes energy loss through optimized use of MOSFETs and DC-DC converters, ensuring effective solar energy harvesting [32,33]. The Adaptive Control enabled by machine learning algorithms allows the system to adjust dynamically to changing conditions, further boosting its efficiency in varying environmental scenarios. Moreover, Remote Accessibility through IoT-enabled communication improves ease of use, facilitates system maintenance, and simplifies troubleshooting, contributing to the overall reliability and convenience of the solar power system.

Software Implementation of the AI-Optimized MPPT Controller

The software implementation for the AI-optimized MPPT controller involves programming both the AI-based control logic and the embedded system firmware. The objective is to implement an intelligent and adaptive algorithm that maximizes the power extraction from the solar panels by leveraging machine learning, fuzzy logic, and genetic algorithms.

MPPT Algorithm Implementation

AI-Based Control Logic

The MPPT controller utilizes an AI-based algorithm that dynamically adjusts the operating point of the solar panel to extract the maximum possible power. This advanced control logic incorporates several AI techniques, each serving a unique purpose to optimize the system's performance:

- **Machine Learning (ML):** ML predicts the Maximum Power Point (MPP) based on historical data, real-time solar irradiance, and temperature conditions. The ML model is trained to identify patterns and adjust the system for optimal power output [42,43].
- **Fuzzy Logic (FL):** FL handles uncertainty and imprecision in environmental factors, such as fluctuating sunlight and temperature, by providing decision-making rules for adjusting the voltage and current. This helps the system adapt to variable conditions effectively [19,20].
- **Genetic Algorithm (GA):** GA is used to dynamically optimize the MPPT control parameters by simulating natural evolutionary processes. The algorithm adapts based on system performance and environmental conditions, ensuring maximum efficiency [21,22].

Implementation in Python/C++

The MPPT algorithm can be implemented in either **Python** or **C++**, depending on system requirements and application stage.

- **Python** is ideal for simulating and training machine learning models. It enables rapid development and testing of AI control logic. Python libraries such as TensorFlow, Scikit-learn, and Keras can be used to train, test, and evaluate ML models, making it a suitable choice for initial development and experimentation.
- **C++** is preferred for embedded applications where performance is critical. It ensures high-performance execution of the AI-based control logic on microcontrollers, offering low-latency control over power electronics. C++ code is optimized for real-time processing and efficient memory management, which is essential for on-device performance [44].

Algorithm Workflow

1. The controller continuously monitors the output voltage and current from the solar panels.
2. AI models process the real-time data to predict the optimal operating point.
3. Control parameters, such as voltage and current, are dynamically adjusted using the selected AI techniques.
4. The power conversion system (DC-DC converters) is adjusted to ensure the solar panel operates at its maximum power point, optimizing the energy conversion process.

Data Processing

AI Model Training

For an effective MPPT control system, AI models must be trained using real-world solar data to accurately predict the optimal operating point of the solar system [45]. The training process begins with **data collection**, where historical solar data—such as solar irradiance, temperature, panel voltage, current, and power output—is gathered from experimental setups, real-world solar farms, or simulated environments. The quality and quantity of this data are vital for training robust models. Following data collection, **preprocessing** is applied to clean and normalize the data, addressing issues like missing values, scaling features (such as voltage and current), and selecting relevant factors that influence power generation. Proper preprocessing ensures that the data is in a suitable form for effective model training. In the next step, **training the model**, supervised learning techniques like regression or neural networks are used to teach the model the relationship between environmental variables (e.g., irradiance and temperature) and the maximum power point (MPP). The model learns to predict the MPP based on these input conditions. After training, the model undergoes **validation and testing** using a separate dataset to evaluate its performance and ensure it generalizes well to new data. If necessary, the model can be fine-tuned or retrained with additional data or improved algorithms. Finally, once the model is optimized, it is **deployed** and integrated into the embedded system's firmware for real-time inference on the microcontroller [46]. This allows the system to dynamically adjust to changing environmental conditions and accurately track the MPP. Through this comprehensive training process, the AI-based MPPT controller can efficiently adapt to varying conditions, ensuring optimal solar energy conversion and maximizing system performance in real time.

Embedded System Programming

a. Microcontroller Firmware Development

The microcontroller firmware is crucial for enabling real-time tracking of the solar panel's performance using an AI-based Maximum Power Point Tracking (MPPT) algorithm [47]. It performs several critical functions to ensure the MPPT controller operates at optimal efficiency. First, it facilitates **real-time data acquisition** by interfacing with voltage and current sensors, collecting live measurements from the solar panel. This data is essential for determining the optimal operating point (Maximum Power Point), allowing the system to dynamically adjust to changes in environmental conditions such as variations in sunlight and temperature. Next, the firmware executes the **control logic** of the AI-based MPPT algorithm, which may include techniques like machine learning, fuzzy logic, or genetic algorithms [48]. This allows the system to continuously adjust the solar panel's operating point in real time to maximize power generation under varying conditions. Additionally, the firmware **integrates with power electronics** by sending control signals to components like MOSFETs and DC-DC converters [34,35]. These signals manage the flow of energy between the solar panel, load, and battery, ensuring efficient power conversion and optimal energy harvesting. Finally, the firmware supports a communication interface for IoT-enabled monitoring, handling communication protocols like Wi-Fi, Bluetooth, or GSM. This enables the transmission of performance data to external devices, such as mobile apps or cloud platforms, which facilitates remote monitoring, analysis, and control of the MPPT system [49]. Through these functions, the firmware ensures the MPPT system is responsive, efficient, and accessible for optimal solar power management.

b. Embedded C/C++ Programming

The microcontroller firmware for the MPPT controller is typically developed using C or C++, which are ideal programming languages for embedded systems due to their low-level control, high performance, and real-time processing capabilities. The development process involves several critical tasks to ensure optimal operation. **Sensor Integration** is one of the primary tasks, where the firmware interfaces with voltage and current sensors, typically using communication protocols like ADC (Analog-to-Digital Conversion) or I2C/SPI. These protocols facilitate accurate measurement of the solar panel's voltage and current, providing the real-time data necessary for power calculations and MPP tracking. **Real-Time Execution** is essential for the firmware to ensure continuous tracking and adjustment of the solar panel's operating point. The control loop needs to execute at a high frequency (e.g., 1 kHz or higher), ensuring that the system can react to environmental changes and maintain system stability without introducing delays that could lead to energy losses [44]. Additionally, Optimization for Memory and Power is a critical aspect of embedded system design. Since embedded systems have limited memory and processing power, the firmware must be optimized for efficient memory usage while minimizing power consumption [36]. This ensures the system operates effectively within these constraints, helping to extend the longevity of the system, especially when powered by renewable energy sources such as solar power. Efficient memory management and low-power

operation are key factors in maximizing system performance and lifespan.

c. Embedded Software Development Tools

Developing embedded system firmware typically involves using specialized tools and integrated development environments (IDEs) to write, debug, and flash the code to the microcontroller. These tools streamline the development process, providing essential support for hardware integration, real-time debugging, and efficient code management. Some of the commonly used tools include:

Arduino IDE: This IDE is widely used for Arduino-based microcontrollers, making it a popular choice for hobbyists and rapid prototyping. It allows developers to write and upload C++ code to the board easily. The Arduino IDE provides a user-friendly interface and supports various libraries, which simplify sensor integration, hardware communication, and peripheral management, making it an excellent choice for simpler or entry-level MPPT system projects [26].

STM32CubeIDE: For STM32-based microcontrollers, STM32CubeIDE offers a more advanced development platform. It enables developers to write, debug, and flash firmware while providing extensive support for the STM32 peripherals, debugging tools, and software libraries specific to the STM32 family. This IDE is particularly suitable for more complex applications requiring high processing power, real-time optimization, and the integration of AI-based techniques such as machine learning, fuzzy logic, or genetic algorithms in MPPT controllers [20].

Both tools offer integrated features that make the development process more efficient, whether working with simpler microcontroller setups or more advanced embedded systems. These IDEs ensure that developers can easily write optimized firmware, debug the system in real-time, and flash the final code to the microcontroller for smooth operation as summarized in Table 3.

Table 3: Summary of the similarities and limitations of Embedded System Programming

Aspect	Microcontroller Firmware Development	Embedded C/C++ Programming	Embedded Software Development Tools
Purpose	Enables real-time tracking of solar panels using AI-based MPPT algorithms.	Provides low-level control, high performance, and real-time processing for firmware development.	Provides an environment for writing, debugging, and flashing firmware to microcontrollers.
Functionality	Acquires real-time sensor data, executes AI-based MPPT control, integrates power electronics, and enables IoT communication.	Supports direct hardware interaction, real-time execution, memory and power optimization.	Streamlines code development, debugging, and microcontroller programming.
Key Features	Implements machine learning, fuzzy logic, and genetic algorithms for MPPT. Interfaces with MOSFETs and DC-DC converters for power management.	Uses ADC, I2C, and SPI for sensor integration. Requires optimization for memory efficiency and low-power operation.	Includes tools like Arduino IDE (for rapid prototyping) and STM32CubeIDE (for advanced real-time processing).
Performance Considerations	Real-time processing ensures optimal power tracking and energy efficiency.	High-speed execution (e.g., 1 kHz control loop) ensures system responsiveness.	Debugging tools optimize firmware performance.
Contrast	Focuses on the firmware's ability to control and monitor the MPPT system efficiently.	Concentrates on how C/C++ provides the necessary low-level programming for firmware development.	Emphasizes the role of IDEs in simplifying and enhancing firmware development.
Limitations	Requires complex algorithm implementation and efficient power management.	C/C++ development can be challenging due to memory constraints and debugging complexity.	Arduino IDE is limited for advanced real-time applications, while STM32CubeIDE requires expertise in embedded system design.

Renewable Energy Integration

The AI-optimized MPPT controller plays a crucial role in enhancing the efficiency, adaptability, and energy management of renewable energy systems [4,51,52,53]. Its integration into various applications—such as off-grid solar systems, hybrid solar-wind systems, and industrial solar-powered factories—results in maximized power output, optimized resource use, and sustainable energy solutions [54,55,56]. Below is a detailed exploration of how the AI-optimized MPPT controller can be effectively integrated into these systems.

Off-Grid Solar Systems: Providing Stable Power Supply for Rural Areas

Off-grid areas, especially in rural regions, often face unreliable access to central power grids, making solar energy a viable solution. However, the variability in solar irradiance and environmental conditions can hinder consistent power generation. AI-optimised MPPT Integration addresses this challenge by enhancing the efficiency and performance of off-grid solar systems. The AI-optimized MPPT controller maximizes power extraction from solar panels, even amidst fluctuating sunlight, by continuously monitoring and adjusting system operations with advanced AI-based algorithms [57,58]. This real-time adaptability ensures high efficiency throughout the day. Additionally, the controller utilizes machine learning techniques to predict power output based on weather variations such as cloud cover and seasonal changes, preventing energy wastage and improving system reliability. By optimizing energy extraction, the system minimizes the need for oversized storage systems, which are often costly in off-grid locations. It also extends battery life by charging at the most efficient voltage, ensuring long-term sustainability [59,60]. The impact of this integration includes improved energy access in rural communities, ensuring a stable and affordable power supply, cost reduction in solar infrastructure and energy storage systems, and enhanced sustainability as solar energy is harnessed more efficiently, reducing reliance on fossil fuels.

Optimizing Energy Utilization from Multiple Renewable Sources

Hybrid solar-wind systems face the challenge of balancing the fluctuating energy outputs from both renewable sources, which are subject to varying weather conditions. Ensuring a consistent energy supply while optimizing the contributions from both solar and wind energy is crucial for maximizing system efficiency [61,62,63]. AI-Optimized MPPT Integration addresses this challenge by providing advanced solutions. The AI-optimized MPPT controller can be seamlessly incorporated into hybrid systems, efficiently managing inputs from both solar and wind energy. Machine learning models predict the most favorable energy source based on real-time data, such as wind speed, solar irradiance, weather forecasts, and historical trends. To balance energy sources, fuzzy logic algorithms enable the system to make real-time decisions, selecting the most effective energy source at any given moment. For example, when wind speeds are low, the system can rely more heavily on solar power, and vice versa, ensuring optimal performance. The controller also adjusts the MPPT for solar panels and optimizes the power point for wind turbines, ensuring cohesive operation across the entire system. Additionally, genetic algorithms fine-tune the control parameters for each energy source, enabling efficient conversion and storage of energy from both wind and solar, ultimately maximizing the overall efficiency of the hybrid system [64,65,66,67,68]. The impact of this integration includes an optimized energy mix from both solar and wind, resulting in a more reliable and consistent power supply, increased energy output as the system maximizes energy generation when one source is more productive than the other, and reduced dependence on external power grids, contributing to greater energy resilience.

Enhancing Energy Management in Solar-Powered Factories

Industrial applications that adopt solar energy often face the challenge of aligning solar power generation with peak demand periods, making it crucial to manage energy output effectively to improve operational efficiency and reduce energy costs [69,70,71]. AI-Optimized MPPT Integration provides a solution by ensuring power supply stability. The AI-optimized MPPT controller keeps solar panels operating at their maximum power point, even with fluctuating environmental conditions such as changes in weather or time of day, ensuring a continuous and reliable energy supply to industrial facilities . The controller also enables peak load management by integrating with energy storage systems to store surplus power generated during daylight hours, which can be used during peak demand periods. Through AI-driven predictions of solar generation patterns, the system schedules energy storage and consumption accordingly, reducing reliance on grid power. Furthermore, the system employs real-time data analysis and machine learning for advanced fault detection and predictive maintenance, identifying anomalies or degradation in solar panel performance. This helps ensure optimal system operation, reducing downtime and extending the system's lifespan. As a result, the AI-controlled system optimizes solar energy usage during peak sunlight hours, reducing grid dependency and significantly lowering electricity costs for industrial operations. The impact includes cost savings through

efficient solar energy use, improved energy management, reduced waste, and enhanced sustainability, as maximizing solar energy reduces the industrial carbon footprint and supports environmental sustainability goals.

Policy Frameworks for Enhancing Thermal Efficiency in AI-Optimized Solar MPPT Controllers for Renewable Energy Microgrids

The evolution of policy frameworks for enhancing thermal efficiency in AI-optimized solar MPPT controllers for renewable energy microgrids has progressed in response to advancements in power electronics, artificial intelligence, and renewable energy integration [72,73,74]]. Early policies primarily focused on general energy efficiency regulations and incentives for solar energy adoption, with minimal emphasis on thermal management in MPPT controllers. As renewable energy deployment expanded in the 2000s and 2010s, governments introduced performance standards for solar inverters and power converters, gradually incorporating thermal efficiency considerations to reduce energy losses [75,76,77,78]. With the rise of AI-driven optimization and smart grid technologies in the 2020s, policymakers have begun addressing the role of intelligent thermal management systems in enhancing MPPT controller efficiency [79,80]. Current regulatory frameworks increasingly emphasize AI-based adaptive cooling mechanisms, thermal resilience in extreme climates, and grid-interactive MPPT technologies, ensuring improved energy conversion efficiency and system longevity. Moving forward, the development of more comprehensive policies integrating AI-driven thermal optimization, standardized testing protocols, and financial incentives will be crucial in accelerating the adoption of high-efficiency MPPT controllers in renewable energy microgrids.

Research Findings

1. **AI-Optimized MPPT Controller Design**: The AI-based MPPT controller developed for this study integrates machine learning, fuzzy logic, and genetic algorithms to dynamically predict and optimize the Maximum Power Point (MPP) under varying environmental conditions. By leveraging historical and real-time solar irradiance and temperature data, the system continuously adjusts voltage and current parameters to ensure maximum power extraction from the photovoltaic system.
2. **Enhanced Adaptability and Efficiency**: Machine learning models, particularly regression-based models and artificial neural networks (ANNs), were used to predict the MPP with high accuracy. The system exhibited superior adaptability to fluctuations in solar irradiance and temperature, resulting in higher energy harvesting efficiency compared to conventional techniques such as Perturb and Observe (P&O) and Incremental Conductance (INC).
3. **Fuzzy Logic and Genetic Algorithm Integration**: Fuzzy logic was utilized to manage uncertainties in environmental conditions, such as variable cloud cover and temperature changes, ensuring smooth system operation without steady-state oscillations. Genetic algorithms (GA) were employed to fine-tune the control parameters dynamically, optimizing the overall MPPT performance. This integration provided real-time adjustments, significantly improving the tracking accuracy under unpredictable conditions.
4. **Comparative Performance Analysis**: The AI-driven MPPT controller outperformed conventional MPPT techniques in terms of efficiency and response time. Under rapidly changing environmental conditions, the AI-based controller exhibited a faster convergence rate and fewer oscillations around the Maximum Power Point. The system's adaptability and precision resulted in a more stable and efficient operation of the PV system.
5. **Scalability for Diverse Applications**: The prototype demonstrated significant potential for scalability in various applications, including rural electrification and industrial energy management. The AI-driven MPPT system can be integrated into off-grid solar systems, hybrid solar-wind power systems, and large-scale industrial applications, optimizing energy generation and reducing reliance on external power sources.

CONCLUSION

The research demonstrates the significant benefits of integrating AI-driven MPPT controllers into photovoltaic systems, offering a more efficient, adaptive, and intelligent solution to power optimization. Machine learning, fuzzy logic, and genetic algorithms provide enhanced performance by enabling real-time adjustments to fluctuations in solar irradiance and temperature, ensuring maximum power extraction and system stability. The AI-based MPPT controller outperforms conventional techniques, offering improved efficiency, reduced energy losses, and higher adaptability, especially in

dynamic environments. This innovative approach holds the potential to revolutionize solar energy systems, particularly in rural and industrial applications, contributing to the advancement of sustainable energy solutions. Future work will focus on further refining the AI models and expanding the application of this technology in various renewable energy systems. Among the conventional MPPT, optimized adaptive differential conductance (OADC) method stands out due to its simplicity, cost-effectiveness, and ease of implementation whereas Scanning Particle Swarm Optimization (SPSO) technique emerges as the most effective, owing to its high tracking accuracy and ability to achieve real-time convergence to the Maximum Power Point. Despite its remarkable efficiency, SPSO is not without drawbacks, including latency in convergence and susceptibility to premature convergence. Therefore, this research recommends further investigations into the Optimized Adaptive Differential Conductance (OADC) and Scanning Particle Swarm Optimization (SPSO) techniques to address and overcome the identified drawbacks. Enhancing these methods will improve their efficiency, power conversion capabilities, and reliability, ultimately advancing the performance of MPPT algorithms in real-world applications.

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